Renewable and Sustainable Energy Reviews 30 (2014) 661–671

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Review of energy models to the development of an efficient industrial energy model

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ARTICLE INFO

Article history:
Received 19 April 2013
Received in revised form
24 September 2013
Accepted 11 November 2013
Available online 30 November 2013

Keywords:
Energy models
Industries
Potential
Policy-makers

ABSTRACT

Presently, there are huge challenges in the presence of the global energy sector, especially in the energy intensive industries that entail a huge collection of energy use, which makes energy security a vital worry. This study analyses various energy models, taking into consideration their various gaps which led to the development of an integrated model for assessing energy efficiency potential in the industrial sector. The resulting developed model will not only serve as a tool for long-term planning to ensure that energy supply is available to meet the demands of targeted economic growth, it will also give policy-makers in the industrial energy management an alertness on how to monitor, control and manage energy consumption.

Contents

1. Introduction

Industries remain a significant contribution to the social and economic growth of a country. In contrast, industries remain indicted for the quick depletion of limited fossil fuels and the pollution of the surroundings [1]. The consumption of energy in industries is due to a series of activities like processing and assembly, space conditioning, and lighting. Natural gas and petroleum products used as feed stocks to generate non-energy products are among industry energy usage [2]. 60% of energy used in industries can be attributed to both developing and countries in economic transition [3]. The utmost consumption of total energy goes to process heating in a manufacturing process. This is followed by machine drives and boiler heating processes [4].

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http://dx.doi.org/10.1016/j.rser.2013.11.007

The interpretation of energy used in the industry is shared into classes of indirect, direct process, and direct non-process uses. Energy consumption varies considerably amongst the various sectors of production in the industries. Around a fifth of universal revenue is created unswervingly by manufacturing industry, and approximately half of the consumption from households depends on products from industries. But upturn in the standard of living made possible through industrial development has emanated at an environmental price. Before the late 1960s, energy use per capita had gone up nine-fold over the previous 200 years as stated and interpreted by UNIDO [5]. Substantial efforts have been created in order to better comprehend the energy efficiency potentials of industries [3]. Increasing energy efficiency in the industries is a crucial basis for green industry globally [5].

To date, energy used in the industries and its efficiency potentials remained predominantly examined by applying energy efficiency indicators and benchmarking methods [3]. The objective of benchmarking has become an important part of the strategic planning process. Industries have to evaluate the energy efficiency of their processes via an international comparison. On the basis of these results, the industries undertake in-depth analyses of their plants to identify further potentials to improve energy efficiency. An important step towards a highly energy efficient facility is a thorough evaluation of a plant's energy efficiency performance and a good knowledge of the existing optimization potentials within a plant [6]. Best practice technology data are obtained from benchmark curves for some sectors. Though, benchmark curves are limited to a portion of universal production, not permitting a comprehensive analysis to be conducted [3]. The differing local conditions also constitute a limitation to benchmarking. The industrial sector and its potential energy saving are thus a focus for the energy future. In the context of this article, a model as an analytical tool to estimate the possible industrial energy potential is reviewed.

Reduction in energy consumption is not a new item on the political agenda. The oil crisis that confronted the industrialized world in the 1970s have forced scientists and policymakers to think about a future that could draw on alternative energy sources and reduce its energy consumption [7].There are several methods for tackling the energy-related problems that impede the sustainable development of our society [7]. One of these methods is to improve the efficiency of energy consumption by developing suitable models for proper analysis and assessment. For energy efficiency potentials to be derived in pursuit of sustainable development, a suitable model is needed which is the focus of this article.

To tackle the tasks of obtaining industrial energy efficiency potential, it is imperative to understand what drives changes in industrial energy consumption [5]. A starting point is by examining some aggregate energy indicators that display energy usage divided by a ration of activity that propels energy demand. This is known as the aggregate final energy intensity. This indicator monitors energy efficiency development [8].

The technical literature of energy model is too broad. This is demonstrated by literature survey and diagnostic examination in print by various researchers. An in-depth appraisal of the literature is therefore outside the area of this research as the focus here is to develop a new model that has the capability to detect or point out opportunities for improving on energy efficiency. A critical review of the past work is undertaken focusing only on literature relevant to the goal of this article. The various models reviewed are based on the following criteria:

(1) Analysis of historical data.
(2) Predicting future energy consumption.
(3) Optimization of energy use for adequate assessment of industrial energy potential.

The next section discusses the relevance of the various energy models to energy analyses and assessment, which is the foundation of this research. Section 3 is devoted to the gaps of the various energy models with respect to their adequacy to detect opportunities for improving energy efficiency within an industry. These gaps form the basis for the design and development of the new model in this work. Section 4 describes the two types of energy efficiency models (micro and macro) with the further derivation of a proposed macro-model, which is a hybrid of IDA–ANN–DEA, to analyze industrial energy use.

2. Relevance of energy models to energy analyses and assessment

Some energy efficiency advocates believe that almost all the problems could be solved, or ameliorated [9] through the use of energy efficiency models. Estimating the potential for energy efficiency improvements and associated energy savings are primary to the preparation, growth, execution and appraisal of energy efficiency [10] models. Energy models were though not established for the similar purposes – some concentrate on improved energy supply system design assuming a level of demand forecast, better comprehension of the current and imminent demand–supply communications, energy and environmental communications, energy–economy communications and energy system planning. Others had concentrated on energy demand analysis and forecasting [11].

Several key questions therefore immediately arise regarding the role of models supporting energy efficiency within a portfolio of prospective energy models. There is a need to know the types of energy efficiency models that have been implemented, and how well has each of these models worked in terms of saving energy? To address the question, we perform a comprehensive review of some macro-economic energy models, with a focus on the development of an efficient model. A huge amount of tools or methods are already established and functional in the literature in the direction of energy efficiency analysis. These methodologies have considered historical data analyses, prediction technique and optimization analysis as assessment criteria. This section develops a working pattern of the analysis and assessment of energy efficiency. It lays the conceptual basis for developing the method for analysis, which can be applied to evaluate energy consumption in the industrial sector. Our analyses suggests that designing a model of energy efficiency potential that accounts for the policy goal of reducing energy consumption will result in considerable savings potential. More importantly, recent experience has shown the potential for energy efficiency and conservation to extensively reduce energy use [10].

3. Various energy models and their gaps

This section focuses on the various energy models and their gaps. These models include decomposition models, predictive models, optimization models and the hybrid models.

3.1. Historical data analysis for energy potential

Regarding analysis of historical data to determine energy saving potential, it appears that decomposing the factors responsible for energy consumption through Index Decomposition Analysis (IDA) has been studied by various researchers for this purpose. The theory of IDA is related to the use of economic index numbers to the analysis of inputs of price and quantity levels to variations in aggregate commodity consumption [12].

The method of decomposition has conventionally been useful to disaggregate changes in an aggregate indicator over time for a country. These authors Ang and Zhang [12,15], Proops et al. [13], Chung [14] have however used the method for cross-country evaluations. There are various index decomposition methods, but the Logarithmic Mean Divisia Index (LMDI) has been the preferred choice.

Among the IDA studies conducted for OECD countries are Howarth et al., and Torvanger [16,17]. In decomposing manufacturing energy consumption change from years 1973 to 1987 in eight OECD countries, Howarth et al. [16], employed the Laspeyres index technique and compared to Divisia technique. Little differences were observed between these two methods as the effects of output, industry structure and energy intensity was explained. Torvanger [17] decomposed the change of carbon dioxide emissions related to energy consumption in nine OECD nations. The author employed the Divisia technique. It was deduced that the reduced energy intensity and the production allocation of energy intensive sectors added to the mitigation of carbon dioxide intensity in the OECD countries examined.

The change of industrial carbon emissions from 36 industrial sectors in China from the time of 1998–2005 was assessed centered on time series decomposition of the LMDI [18]. The outcomes of their study showed that raw chemical materials and chemical products, non-metal mineral products and smelting and pressing of ferrous metals accounted for 59.31% of aggregated increase of industrial carbon dioxide emitted. The great participants to the change of China's industrial sectors' carbon emissions in that time were the industrial activity and energy intensity; the impact of emission coefficients of heat and electricity, fuel shift and structural shift was relatively small.

The decomposition of industrial energy usage in Singapore at two stages of disaggregation is investigated by Ang [19]. The influence of structural change and changes in sectoral energy efficiencies is inspected for Singapore and Taiwan [20].

Salta et al. [21] employed LMDI decomposition analysis to evaluate the influence of the production, structure and energy efficiency effects to changes in sub-sectoral manufacturing energy to selected sub-sectors of the Greek manufacturing sector from 1985 to 2002 for electricity, fossil fuels and total energy use. Another study that deals with the decomposition analysis of energy-related carbon dioxide emissions in Greece was carried out by Hatzigeorgiou et al. [22] from 1990 to 2002. The Arithmetic Mean Divisia Index (AMDI) and LMDI methods were employed and changes in carbon dioxide emissions are decomposed into income effect, energy intensity effect, and fuel share effect. The period-wise and time series analyses show that the prime contributor to the rise in carbon dioxide emissions is the income effect; on contrary, the energy intensity effect is primarily accountable for the decrease in carbon dioxide emissions. Bohm [23] analyzed the relationship between emission growth and changes in underlying factors using the LMDI method. The study covered the biggest carbon dioxide emitting countries and regions that together account for over 80% of total emissions worldwide in the period from 1971 to 2005. The results illustrate that GDP growth is by far the prime contributor to global emissions followed by an increasing population, whereas decreasing energy intensity was and still is the most vital factor to mitigate emissions. Thus, a common respond to reducing energy consumption and pollution effect to determine and assess possible energy potential is to decompose the factors responsible to establish their contribution to energy consumption.

3.2. Prediction analysis for energy potential

For a better understanding of energy use and future energy requirements, it is important to understand the causal factors [11]. This has been successfully achieved with the use of IDA. However, such analyses fail to capture the baseline of energy use and its forecast which is required for potential assessment. ANNs are useful tool in this respect. For example, Wong et al. [24] developed ANN model for office buildings with day-lighting for subtropical climates. In their analysis, the comparisons between the annual and seasonal error analysis of cooling and heating electricity consumption suggested that the ANN model developed has more accurate predictions of electricity use for periods during which a particular end-use exhibited substantial demand (i.e. summer cooling and winter heating). To predict regional load in Taiwan [25] and greenhouse gases in Turkey [26]. Based on the forecast results of Hsu and Chen [25], some suggestions for Taiwan power market providers were presented. The result showed that the power market providers facing the power facilities construction location problem should consider the northern and southern regions of Taiwan first in future planning. The results of the study of Sozen et al. [26] showed that the prediction formula of ANN with high confidence dependent on sectoral energy consumption can use GHG emissions in Turkey in order to determine the future level of GHGs.

Analyzing and predicting wind power generation [27], prediction of net energy consumption in Turkey [28] and the forecasting of daily electric load profiles of a suburban area [29] are among the ANN studies performed. Wind energy engineers are interested in studies that aim at assessing the output of wind farms [27], for which, the techniques of artificial intelligence was successfully adapted. The ANN model shows a good agreement with the actual values. The model was found to be helpful for energy planners and wind farm owners for future planning and execution. The study of Sozen and Arcaklioglu [28] was to obtain equations based on economic indicators (gross national product –GNP and gross domestic product – GDP) and population increase to predict the net energy consumption of Turkey using ANNs in order to determine future level of the energy consumption and make true investments in Turkey. Based on the outputs of the study, the ANN model can be used to estimate the net energy consumption from the country's population and economic indicators with high confidence for planning future projections. The influence of climate variability on the electricity consumption [29] was investigated. ANN was trained using weather data (temperature, relative humidity, global solar radiation) along with historical data available for a part of the electric grid of the town of Palermo (Italy) from 2001 to 2003. The results obtained bore out the suitability of the adopted methodology for the short term load forecasting problems.

ANN is employed to model the energy usage of appliances, lighting, and space-cooling in Canadian residential sector [30]. Turkey is predicted using the ANN technique [31]. Two models have been employed in the Turkey prediction: population, gross generation, installed capacity and years are used as variables for the input layer of the network for the first model and other energy sources are used in input layer of network for the second model.

The global key energy consumption including fossil fuels such as coal, oil and natural gas has been thought about for the study of global green energy consumption through ANN [32]. The investigation made a case that green energy can be considered as a means for energy security, sustainable development, and social, technological, industrial and economic development.

The energy requirement for South Korea is forecasted using a feed forward multilayer perceptron, error back propagation technique [33]. The model took into consideration gross domestic product, population, import and export. The results are evaluated with the multiple linear and exponential regression energy demand models. The Greek long-term energy consumption is forecasted using ANN multilayer perceptron model. The input

parameters chosen are yearly ambient temperature, installed power capacity, yearly per resident electricity, consumption, gross domestic product [34].

Gorucu and Gumrah [35] have used ANN to forecast the gas demand for Ankara. GNP, population and vehicle kilometer are used as input variables in training ANN model for forecasting the transport energy requirement for Turkey [36]. The transport energy demand usage in Thailand is established using the national gross domestic product, population and the numbers of registered vehicles as independent parameters [37]. Log-linear regression models and feed-forward neural network models are used in the investigation. Azadeh et al. [38] have employed ANN for predicting the yearly electricity usage in high energy consuming industries in Iran. The ANN method is based on a multilayer perceptron model. The precision of the ANN results over regression models are confirmed by means of ANOVA. Olanrewaju et al. [39] have utilized ANN model for predicting the energy usage in the industrial sector of South Africa between 1993 and 2000. The study looked at energy consumption under economic activity, GDP. Their results signified intense conformity between ANN model prediction and observed values compared to linear regression model. One may judge a forecast successful if it (a) helps energy planners and (b) influence the energy policy community [11].

3.3. Optimization analysis for energy potential

Wrong forecasts can lead to wrong decisions [40], thus predictive analysis with reliable and relevant obtained results can serve as an aid for recommending and specifying opportunities to reduce irrational energy use [41]. On the other hand, for a complete analyses of energy potential, energy baseline determination and its forecast is not sufficient to capture the potentials of energy efficiency. Analyzing the several factors leading to energy consumption and optimization by minimizing these factors and other input factors to energy consumption becomes necessary.

Data Envelopment Analysis (DEA) has been applied to much energy related studies as an optimization tool to assess the possible energy saving potential. Chauhan et al. [42] determined the efficiencies of farmers with regard to energy in rice production activities using the DEA approach. The study showed that about 11.6% of the total energy consumption could be saved if the farmers follow the input package recommended by the study. Hu and Kao [43] found the energy-savings target using DEA for APEC economies without reducing their maximum potential gross domestic productions in each year. It was found that China had the largest energy-saving targets. Lieu et al. [44] evaluated the thermal power plant operational performance in Taiwan using data envelopment analysis. The power plants studied achieved acceptable overall operational efficiencies during 2004–2006, and the combined cycle power plants were the most efficient among all plants.

The performance of electricity generation plants in Turkey was analyzed and compared [45] using DEA. Interesting conclusions regarding renewable power plants, thermal power plants investment performance and thermal power plants operational performance were drawn. Shi et al. [46] used DEA in their study to measure Chinese industrial energy efficiency and investigated the maximum energy-saving potential in 28 administrative regions in China, considering the issues of undesirable outputs and minimization of energy consumption. Based on their findings, they were able to propose some policies to improve regional industrial energy efficiency in China.

In assessing modifications in total productivity, splitting it down into technically efficient and technological change, DEA has been successfully applied to the hydroelectric energy generating plants of the EDP – the Portugal Electricity Company. The study intended to sought after the optimal practices that would lead to advanced performance in the energy market [47].

In a study to benchmark the energy performance of buildings, Lee and Lee applied DEA as an amendment to the conventional approach. Their study assessed 47 government office buildings in Taiwan. Based on the examination of their study, five evaluated buildings report least energy usage in different levels and are graded as 100% for the optimal management performance. Six buildings received the rating of 80–99%, 23 buildings were below 60% and the worst was 31%. The average indicator of energy performance of all evaluated buildings reads 65% [48]. A study estimating the efficiency of electric power generation in the United States for the period of 1991 through 2004 using DEA [49] has been a success. The acquired results depict a relative firmness in efficiency of 99–100% from 1994 through 2000 with an acute reduction to 94–95% levels in the years following. Through the various studies, it has been a commonplace among the researchers that optimizing those factors responsible for energy consumption would lead to realize the possible energy saving potential.

3.4. Hybrid models for energy potentials

Computing the efficiency and minimizing energy resources with the DEA model are very useful to understanding how best energy should be consumed. However, without proper analysis of the causal effects and its baseline determination, a limitation to DEA, it becomes difficult to have an effective assessment for energy efficiency potential.

In the literature, hybrid models have been employed as an alternative approach to energy studies. Studies like Azadeh et al., Ebrahimpour et al., and Lee [50–52] among others have made attempts to realize a hybrid system using various techniques. The integration of these methods seems to proffer merely ad hoc results. None of these hybrid models are based on a unified system. Their contributions however cannot be left unidentified.

The study of Azadeh et al. [50] introduced an integrated approach based on DEA, principal component analysis (PCA) and numerical taxonomy (NT) for total energy efficiency assessment and optimization in energy intensive manufacturing sectors. The results of the proposed approach end into ranking of manufacturing sectors, verification, optimization and determination of critical indicators.

Ebrahimipour et al. [51] presented a framework for ranking of power sector's performance based on machinery productivity indicators. The combination of Genetic Algorithm (GA), PCA and NT are effectively used for all branches of power sector to rank this sector of industry. According to the authors, the developed approach of their study could be used for continuous assessment and improvement of power sector's performance in supplying energy with respect to overall productivity and reliability aspects (expected energy not supplied).

Lee [52] examined the effectiveness of energy management using multiple linear regression method with DEA. The government office buildings in Taiwan were used as a case study. The results show that most of the buildings evaluated reported a higher predicted energy usage intensity and have successfully used efficient energy management methods in energy saving. Olanrewaju et al. [53] used Artificial Neural Network combined with Data Envelopment Analysis as a management technique that uses energy information as a basis to eliminate waste, reduce and control current level of energy use in South African industrial sector.

Azadeh et al. [54] presented a flexible approach that comprises ANN and fuzzy data envelopment analysis (FDEA) that was successfully applied for location optimization of solar plants in Iran. It was concluded that the approach would assist

policymakers to recognize the preferable approach for locating optimization problems attached with solar plant units. Another research adopting a neuro-fuzzy stochastic frontier analysis for long-term natural gas consumption prediction and analysis of the behavior of natural gas consumption has been investigated. The approach proved to be capable of dealing with complexity, uncertainty, and randomness as well as several other unique features as referred to in the study of Azadeh et al. [55].

The integration of DEA, corrected ordinary least squares (COLS), stochastic frontier analysis (SFA), principal component analysis (PCA) and numerical taxonomy (NT) method has been a success for assessing the performance, optimizing and creating policy for electricity distribution units in Iran. The integrated model features have proved to be flexible and comprehensive for the particular study [56]. Where crude oil has played a noteworthy part in world economy, Yu et al. [57] proposed an empirical decomposition (EMD) based neural network for the purpose of world crude oil spot price prediction. The proposed technique proved its uniqueness compared to other techniques in terms of its root mean square error. A model based on ANN and regression analysis has been proposed by Kankal et al. [58] for the advancement of modeling energy use in Turkey mainly on GDP, population, import and export amounts (socio-economic and demographic variables).

Azadeh et al. introduced fuzzy regression-data envelopment analysis algorithm for the estimation and optimization of oil consumption. It was successfully applied on a monthly basis from 1990 to 2005 for Canada, United States, Japan and Australia. The integrated model guarantees optimum solution due to its integrated mechanism and flexibility which searches for the best fuzzy regression model through a standard scientific mechanism [59]. For an improved estimation of electricity consumption, Kheirkhah et al., developed ANN–PCA–DEA–ANOVA algorithm. The hybrid model was applied to Iranian electricity consumption using data from April 1992 to February 2004. Each of the integrated models has its unique intelligent function for an improved estimation of electricity consumed [60].

Use of combined approaches is beneficial as “these techniques seem to be able to take advantage of the best characteristics of all the techniques which comprise the combination”. Combining different approaches allows biases in one technique to offset biases in other techniques [11].

Integration of models has been a success in the energy studies. Though, the integration of the right models is yet to be formulated for accurate energy potential analyses. Modelers are often pressed to give a single answer to a particular question [61], which most integrated models do. Thus, for proper energy analysis, there are many questions that need answers for a complete assessment of energy consumption for its potential. This research describes a management system tool that uses a basic mechanism allowing a tight integration of historical data analysis, prediction capability, and efficiency computation and optimization capability as an approach for assessment of energy consumption in an industrial sector, thus, guarantees advanced efficiency. This becomes the focus of this research, integrating IDA, DEA and ANN to assist in constructing systems for proper energy management in the industrial sector.

4. Derivation of the proposed model

Mathematical models are significant. On one hand, they force quantification of the variables at play in the energy phenomenon and dynamics. On the other, they allow for the use of mathematical methods to better understand the inter-play between the state variables and the behavior of the phenomenon.

Models demand simplicity. Energy models communicate those aspects regarded as critical or typically related to energy efficiency. It will be established that micro and macro-models are used to assess energy efficiency potentials. Improving the energy efficiency of specific technology type is considered as micro-models whereas macro-models have a detailed representation of energy use but limited detail to represent industrial process. The macro-models include the industrial sector, while some of the micro-models address specific applications in the industry (i.e., motors). In relation to policy-making, energy models can be said to be used for two main purposes among others; namely to supply vital information on energy problems in order to enable policymakers to value their seriousness and to support policy development and priority setting, by identifying key factors that cause pressure regarding energy.

Energy efficiency model is a very broad area ranging from specific equipment to particular sectors. Various energy efficiency models often conform to similar energy activities. Effective representation and characterization of energy use can be facilitated by mathematical modeling.

In order to successfully assess possible energy potential, it is imperative to develop a mathematical model that will analyze the historical energy data, predict the expected energy to be consumed to determine the baseline and later optimize the present energy use with reference to the predicted baseline.

The mathematical model is to represent the state variables of an industrial energy use which presents the outcome of possible energy potential. It is a commonplace that there is a great interest in the amount of energy used to produce an output in an industrial process. In the various industrial processes, there are factors responsible for the consumption of energy, whereas, the energy consumed is usually regarded as a limited resource. Therefore, any modeling of industrial consumption of energy typically involves a mathematical description of the interaction of various factors.

Toward this study, the description of the interaction of various factors with energy is limited to activity, structure and intensity for the aggregated industrial energy consumption purposes. Where energy saving is imperative, energy models give avenue for such opportunities.

4.1. Micro and macro-model

In the previous years, energy efficiency in industrial process has attracted governments, and progressively they have been keen to exploit it [62]. This has led to different models, i.e., micro and macro-models. There exists a variety of available ‘macro’ tools and models. Some tackle detailed applications or specific sectors. They vary from GHG inventory models to screening models that approximate the emission effects of different energy policies to models which appraise energy efficiency potential within a region. A second class of tools is obtainable to tackle definite technology types or energy supply sectors [63]. Collectively, industrial equipment uses a lot of energy. Consequently, small inefficiencies in industrial parts at plant level can lead to high energy waste on a national scale. However, investing in more energy efficient equipment is simply not a primary concern [64], rather the improvement of existing equipment.

Building a macro-model to stand for provisional energy usage and emissions offers a huge amount of advantages. There are multi-fuel, multi-sector energy and emission models that can model policy impacts across the economy. These models make it relatively easy to identify where there is significant impact on energy use and emissions. The procedure of collecting, reviewing and analyzing the data needed for such models provides an opening to have a better comprehension of the dynamics responsible for energy consumption and obstacles to varying current

forms of energy use [63]. Most macro-economic models focus on energy intensity as a parameter [7].

Micro-models on the other hand is used to give a more thorough look at energy used and assist as an input to the macro-level model. Micro-models can be used to both inform the macro-model and to extend and improve macro-level analyses for particular sectors or applications [63]. Micro-methods are based on the technology used; focusing on heat conversion efficiency, heat loss, electric motor efficiency, etc. [7]. Industrial equipment like motor systems and other electric devices fall into this category. Motors and other electric appliances function at the utmost efficiency when the power received is the right voltage, phase balanced, and distortion free. Amenities can retain their power in proper state by fixing damaged end-use equipment to enhance the power factor and reduce line voltage fluctuations. These tune-ups can offer small, but cost-effective gains in energy efficiency, equipment performance, process control, and reduced downtime [65]. Improving electric motor systems, include [66] – use of high efficiency electric motors; correct sizing of the motor to match load requirements; use of variable speed drives (VSD) where there is a variable load, to match motor speed and torque to load requirements; use of high efficiency couplings between the motor and driven machine; proper maintenance and repair [64].

Macro-models have some advantages over the micro-methods. First, macro-models are very suitable for evaluating the possible development of the demand for energy if no policy measures are taken to stimulate energy efficiency improvement. Second, with most models, the potential effect on the energy demand of changing the energy price can also be evaluated. Finally, macro-effects of investing in energy efficiency improvement can be assessed in principle [7]. All models offer a simplified illustration of actuality. The capacity to project the impact of changing the decisions which determine energy consumption by way of policies and initiatives is subject to the level of detail illustrated in the model [63].

4.2. Proposed model

This section presents the design framework emerging from the proposed design of this study. This model looks at the direct effect of three variables, i.e., activity, structure and intensity on realizing energy potentials in an industrial sector. A model has been developed for historical analysis of energy consumption to determine possible energy potentials. Additional models predict and others are developed to optimize variables responsible for energy consumption. Therefore, this section discusses the proposed hybrid model. The goal of this section is to propose a model to analyze the impact of these variables on industrial energy consumption for possible energy potential saving.

4.2.1. Assumption to the model

The integrated model is based on the assumption that the results of IDA must be non-negative. Therefore, if the results from the IDA are negative, the integrated model will not be applicable. Multiplicative decomposition method must be the preferred IDA to be integrated to the model, since its results are non-negative. The non-negativity value is as a result of DEA's involvement in the model.

4.2.2. Model derivation

The scope and methodological characteristics of a particular model depend on the specific policy or planning concerns addressed by it [67]. This study is concerned with the planning concerns specific to the industry as a whole, which led to the formulation of a macro-model developed for this research.

The conceptual framework for the present study is presented in Fig. 1. The independent variables are the activity, structure and intensity. The dependent variable is the energy consumption. As the conceptual framework indicates, the dependent variable was decomposed into the various independent variables with the aid of IDA. The dependent variable is predicted to determine the baseline energy consumption using the independent variables as input drivers to the ANN. Validating the baseline result will enable DEA to perform a sensitivity analysis to determine the possible energy potential available.

Consequently, the model derivation follows. The input data obtained from the industry using multiplicative decomposition method is given below:

The variables used for the decomposition analysis

E_i – total energy consumption in sector/or department i
E – total energy consumption ($E=\sum_i E_i$)
Q_i – value of production in sector/or department i
Q – total value of production ($Q=\sum_i Q_i$)
S_i – production share of sector/or department I ($S_i = Q_i/Q$)

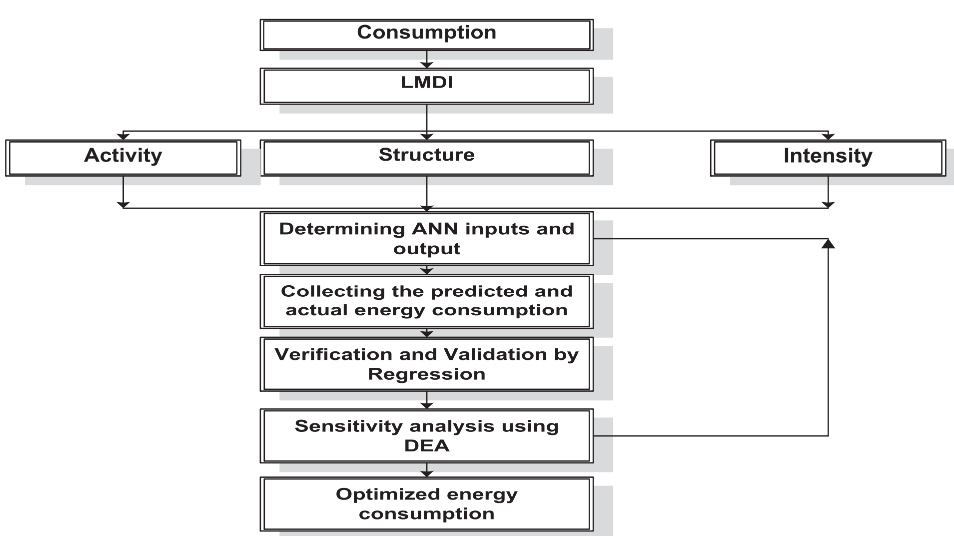

Fig. 1. Schematic framework of the general proposed model.

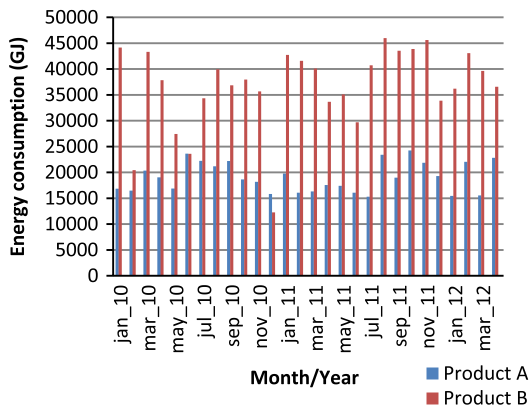

Fig. 2. Energy consumption data.

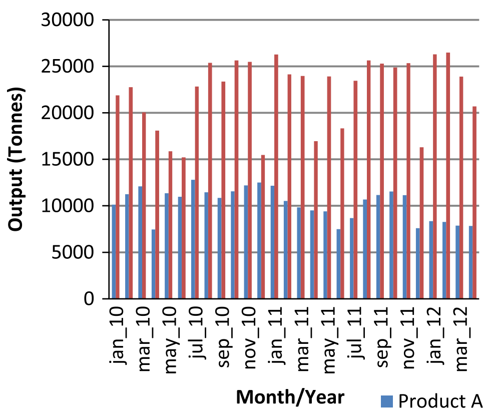

Fig. 3. Output data.

I_i – intensity of energy consumption in sector/or department ($I_i = E_i/Q_i$)

$$E = \sum_i E_i = \sum_i Q\frac{Q_i}{Q}\frac{E_i}{Q_i} = \sum_i QS_iI_i \tag{1}$$

$$E^T - E^0 = \Delta E_{tot} = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} \tag{2}$$

$$\frac{E^T}{E^0} = D_{tot} = D_{act}D_{str}D_{int} \tag{3}$$

where D_{tot} is the total energy consumption, D_{act} is the activity, D_{str} is the structure and D_{int} is the intensity.

$$D_{act} = \exp\left[\sum_i w_i \ln\left[\frac{Q^T}{Q^0}\right]\right]; \tag{4}$$

$$D_{str} = \exp\left[\sum_i w_i \ln\left[\frac{S_i^T}{S_i^0}\right]\right]; \tag{5}$$

$$D_{int} = \exp\left[\sum_i w_i \ln\left[\frac{I_i^T}{I_i^0}\right]\right]; \tag{6}$$

$$U_{tot} = D_{act} + D_{str} + D_{int} \tag{7}$$

the multiplicative decomposition variables serve as input to ANN, whose equation is given by

$$y_j = f(\sum_i w_{ij}x_{ij}) \tag{8}$$

Substituting the variables (Eqs. 4–6) as input values and Eq. (7) as the output value into Eq. (8) becomes

$$U_{tot} = f\left(\sum_i w_{ij}\{D_{act(ij)}, D_{str(ij)}, D_{int(ij)}\}\right) \tag{9}$$

the goal is to minimize the average sum of the errors between the decomposed energy consumption (output to the neural network) and the target energy consumption (predicted baseline energy consumption). Thus,

$$mse = \frac{1}{Q}\sum_{K=1}^{Q}[U_{tot}t(k) - U_{tot}a(k)]^2 \tag{10}$$

where $U_{tot}t$ is the predicted baseline total energy consumption and $U_{tot}a$, the decomposed total energy consumption.

From the DEA equation (interested readers can refer to [68]); substituting $U_{tot}(t)$ as the output variable and $U_{tot}(a)$ as the input variable gives

$$\begin{aligned} &\text{Max } \frac{\sum_{r=1}^{s} U_{tot}(t)_{ro}u_r}{\sum_{i=1}^{m} U_{tot}(a)_{io}v_i} \\ &\text{s.t } \frac{\sum_{r=1}^{s} U_{tot}(t)_{ro}u_r}{\sum_{i=1}^{m} U_{tot}(a)_{io}v_i} \le 1, \quad j = 1\ldots n \\ &v_i \ge 0, \quad i = 1, \ldots, m; \\ &u_r \ge 0, \quad r = 1, \ldots, s. \end{aligned} \tag{11}$$

where $U_{tot}(t)_{ro}$, $r = 1,\ldots s$ represent outputs and $U_{tot}(a)_{io}$, $i = 1,\ldots m$, represent inputs for each of $j = 1,\ldots n$, DMUs and $j = 0$ identifies DMUj to be evaluated. μ_r is the output weight while v_i is the input weight. Transforming into an ordinary linear programming problem, thus;

$\mu_r = \beta\mu_r$, $v_i = \beta v_i$ is obtained with the same optimum value as (11)

$$\begin{aligned} &\text{Max } \varphi = \sum_{r=1}^{s} \mu_r U_{tot}(t)_{ro} \\ &\text{Such that } \sum_{i=1}^{m} v_i U_{tot}(a)_{io} = 1, \\ &-\sum_{i=1}^{m} U_{tot}(a)_{ij} + \sum_{r=1}^{s} \mu_r U_{tot}(t)_{rj} \le 0, \quad j = 1, \ldots n, \\ &v_i \ge 0, \quad i = 1, ..m, \\ &\mu_r \ge 0, \quad r = 1, \ldots s. \end{aligned} \tag{12}$$

Eq. (12) has a dual form that can be written as

$$\begin{aligned} &\text{Min } \eta_o \\ &\text{Such that } \sum_{j=1}^{n} U_{tot}(a)_{ij}\lambda_i \le U_{tot}(a)_{io}\eta_o, \quad i = 1, \ldots, m \\ &\sum_{j=1}^{n} U_{tot}(t)_{ij}\lambda_j \ge U_{tot}(t)_{ro}, r = 1, \ldots s \\ &\lambda_j \ge 0, \quad j = 1, \ldots, n \end{aligned} \tag{13}$$

Eqs. (12) and (13) will allow the accountability for the extra energy consumed while keeping the expected energy to be consumed at the baseline level. This model derived has been utilized in various case studies.

4.2.3. *Case study example: assessing energy consumption in a food and beverage industry ABC: integrated IDA–ANN–DEA approach*

In this case study, we analyzed a specific food and beverage industry ABC Pty between January 2010 and April 2012 of one of the South African food and beverage industries. Data used, Figs. 2 and 3 show the energy consumption and output production data used for this study. The productions are all given in tonnes and the energy consumption in gigajoules.

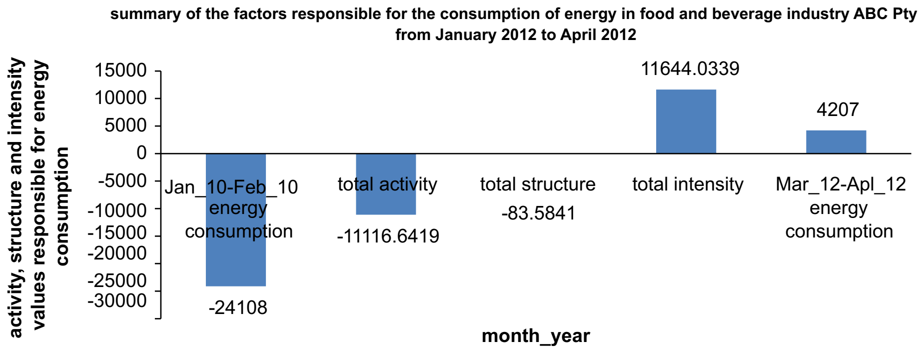

Fig. 4. Summary of the factors responsible for the consumption of energy in food and beverage industry ABC.

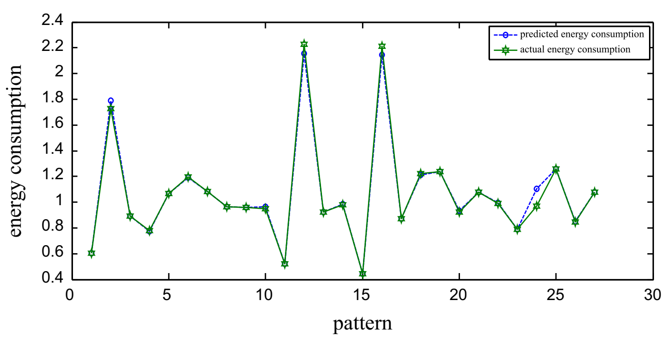

Fig. 5. Prediction result for energy baseline.

Table 1
Efficiency scores based on benchmarking of the food and beverage industry ABC.

DMU no.	DMU name	Efficiency
1	Jan10–Feb10	0.88120
2	Feb10–Mar10	0.91460
3	Mar10–Apl10	0.88120
4	Apl10–May10	0.87554
5	May10–Jun10	0.88120
6	Jun10–Jul10	0.87738
7	Jul10–Aug10	0.88120
8	Aug10–Sep10	0.88129
9	Sep10–Oct10	0.88120
10	Oct10–Nov10	0.89121
11	Nov10–Dec10	0.88120
12	Dec10–Jan11	0.85321
13	Jan11–Feb11	0.88120
14	Feb11–Mar11	0.88480
15	Mar11–Apl11	0.88120
16	Apl11–May11	0.85538
17	May11–Jun11	0.88120
18	Jun11–Jul11	0.87256
19	Jul11–Aug11	0.88120
20	Aug11–Sep11	0.89362
21	Sep11–Oct11	0.88120
22	Oct11–Nov11	0.88645
23	Nov11–Dec11	0.88120
24	Dec11–Jan12	1.00000
25	Jan12–Feb12	0.88120
26	Feb12–Mar12	0.88473
27	Mar12–Apl12	0.88120

4.2.3.1. Results from analysis. Applying the index decomposition analysis, from Fig. 4 below, the consumption of energy from period January 2010 to February 2010 has increased by 673% by March 2012 to April 2012 period. For activity effect, changes in the level of activity between 2010 and 2012 are considered, keeping the intensity and share of food and beverage industry ABC Pty in value addition unchanged in the initial year values. This implies that if activity would have changed alone, the energy demand for the food industry activities considered would have reduced by 11,116.6 GJ.

For the structure effect, the structural change within the period is considered while keeping the other two factors unchanged. This suggests that the share of the food industry's activities in the industrial output has reduced and if this only had changed, the energy demand would have reduced 83.58 GJ.

Finally for the intensity effect, we look at the changes in energy intensity within the period under investigation and keep the other two factors at their initial values. This suggests that the intensity in the food industry has increased and their intensity would have increased the energy demand by 11,644 GJ between 2010 and 2012 if other things did not change. It can be concluded that from the period under investigation, energy has not been consumed efficiently.

For the prediction technique; activity, structure and intensity were the inputs while the actual energy consumption was the output. It was discovered that a strong correlation exists between the baseline (predicted energy consumption) and the actual energy consumption. Fig. 5 presents the results.

To confirm and validate the ANN's result, linear regression analyses is a likely confirmation method to the neural network model between the predicted and corresponding energy consumption values. The analyses lead to a line $y=a+bx$ with a correlation coefficient of R^2. A perfect prediction would give, $b=1$ and $R^2=1$. From the validation result, $b=0.985$ and $R^2=0.996$.

To be able to determine the possible energy saving for the period of study, DEA analysis was carried out. The observed energy consumption was selected as the input whereas the predicted energy consumption was selected as the output data for the analyses. The efficiency scores of the food and beverage industry ABC in different months/years (DMUs) are shown in Table 1. These efficiency scores are relative to the best performing months/years.

“Sensitivity analyses” on Eq. (13) has been applied. For example, food and beverage industry in January 2010–Feruary 2010 will encounter a potential savings of $(100-88.12=11.88)$ % in energy consumption compared to the best practice in December 2011–January 2012. Food and beverage industry in January 2010–February 2010 can reduce their energy consumption by 11.88% and become efficient. Fig. 6 relates the consumption to the percentage amount of energy that would have been saved if the periods emulated December 2011–January 2012 practice. In summary, the amount of energy that could have been possibly saved is 11% of the total energy consumed for the whole period under study, which is equivalent to 171,533.78 GJ.

Table 2 shows the results of the proposed model in various studies of application. The proposed model's features are

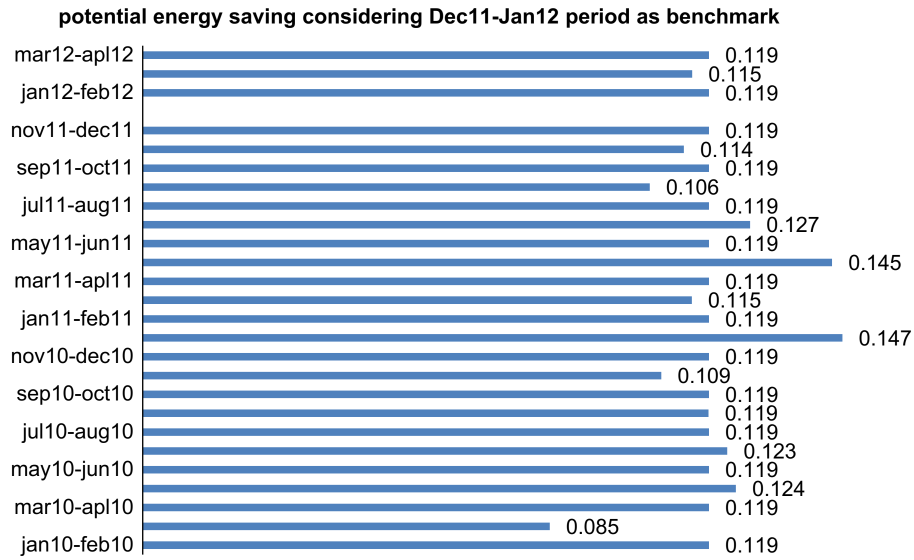

Fig. 6. Potential energy saving for food and beverage industry ABC.

Table 2
Application of the model in various studies.

Model	Application	Possible potential that can be saved
Proposed model	Canadian Industrial Sector [69]	0.47% of energy consumed
Proposed model	South African Industrial Sector	44.9% of energy consumed
Proposed model	A particular food and beverage industry ABC Pty in South Africa	11% of energy consumed

Table 3
Comparison of the proposed model against existing models [69].

Existing models	Significant features			
	Efficiency computation	Analyzing historical data	Prediction capability	Optimization capability
Proposed algorithm	√	√	√	√
DEA	√			√
ANN	√		√	√
IDA		√		

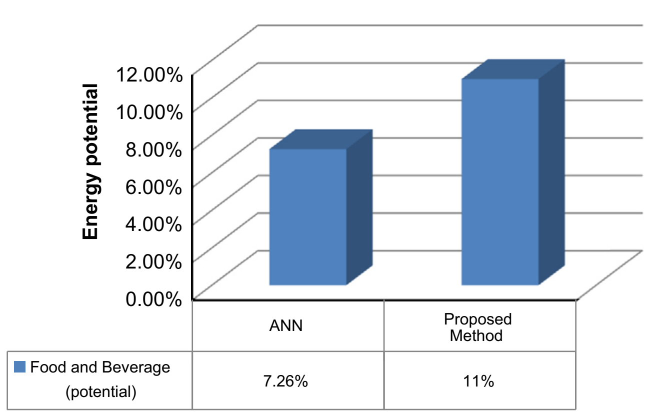

Fig. 7. Comparison of the proposed model against artificial neural network.

compared with other models in Table 3 to identify the better energy potential assessment model. Fig. 7 shows its comparison with artificial neural network. In its comparison, the proposed method was able to identify more potentials than its competitor. This is because it is not based on *apriori* assumption. In computing the amount of potential energy saving using the artificial neural network, a decision making unit (DMU) with the largest error was used for other DMUs in calculating their efficiencies while the proposed model considered all DMUs.

5. Conclusion

IDA, ANN, DEA and hybrid models are all powerful analytical tools as presented, but have their weaknesses and limitations. Based on our survey, these models could be helpful to researchers in energy issues like identifying the relative contributions of different factors to changes in energy demand, prediction and forecasting of energy consumption for short- and long-term planning. Benchmarking performance to determine the potential of energy that could be saved has also been explored among the various industries. This research underlines the gaps of the individual energy models as far as energy analysis is concerned, and highlights the reasons why integration of the right models is necessary.

To analyze energy efficiency potential, it is necessary to develop a theory for the model. All energy model theories are based to some extent on empirical observation, if only for certain basic assumptions. Thus, this article provided a basis for the development of a new hybrid energy model theory for potential assessment, and its various equations analyzed. To analyze and assess the energy efficiency potential, the proposed algorithm will serve as a management technique to analyze historical data, predict the future energy consumption, optimize the use of energy and compute energy efficiency to eliminate waste, reduce and control current level of energy use compared to the existing methods.

To easily identify possible energy potentials in the industrial sector, an integrated model has been successfully developed. Each integrated model with its advantages was designed to offset the disadvantages of other models. Integration of IDA is to decompose the consumed energy to the various factors responsible for energy consumption. ANN is to predict the baseline as a benchmark for DEA to determine the possible potential.

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